MSG-SET-183 Specialists' Meeting – Improving the Simulations of Radar Signatures of Small Drone

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ABSTRACT

Small drones have attracted significant research interest from law enforcement and defence agencies due to the challenge in detecting, tracking, and classifying them with radar, because of their small size and high manoeuvrability. As collecting experimental data for all possible drone models and scenarios is unfeasible, modelling work to simulate accurately the signatures of these platforms is an important task. This paper presents some preliminary results of research effort to enhance modelling capabilities of the radar signatures of individual small drones, and multiple drones flying together in the scene of interest.

1.0 INTRODUCTION

Small drones have become increasingly popular in recent years and used for a variety of applications by commercial companies and private hobbyists. These may include inspection of remote areas or structures, agricultural monitoring, professional photography and filming, search and rescue, police surveillance, and even delivery by the logistics and retail sectors. It is expected that this trend of increased usage of small drones will continue, supported by developments in navigation sensors, better batteries, and improvements in flight control and autonomy.

Conversely, there are significant concerns from law enforcement and security agencies with respect to the misuse of small drones, either accidentally or on purpose. Activities such as illegal filming and reconnaissance of restricted areas, trafficking of illegal substances, collision hazard with assets on the ground or larger aircraft, and "weaponised drones" carrying chemicals or explosive payloads can be empowered by the usage of small drones. As an example, in the days before Christmas 2018, Gatwick Airport, one of the busiest in the United Kingdom, was brought to a standstill of several hours due to the presence of drone(s) in its airspace, causing very significant economic loss and discomfort to many travellers. As the flight autonomy of individual drones and their embedded intelligence for performing tasks independently from human controllers' inputs increase, the aforementioned threats and concerns are expected only to increase. The possibilities of coordination of several drones in swarms will further exacerbate such issues.

For these reasons, significant research effort has been devoted to develop techniques to detect, monitor, and when needed neutralise possible "rogue" drones. Radar technology is of interest in this domain, as it can provide monitoring capabilities at long distances and in any weather or lighting conditions, with little if no effect caused by fog, rain, darkness, smoke (at least at the lowest frequency bands typically used for long range monitoring of larger aircraft). Furthermore, range-Doppler processing already developed for larger aircraft can potentially be used for drones as well, with relatively simple algorithms to estimate presence, number, position, and velocity of drones. In addition to that, micro-Doppler processing based on the specific signature of drones' blades and propellers can further enhance the classification of different models of drones, their discrimination against birds, and potentially enable payloads detection [1-7].

However, the challenge of using radar in this application is posed by the small size of drones and their highly manoeuvrable flight patterns. This translates in rather low radar cross section, compromising detection capabilities, and in difficult tracking if conventional approaches designed for larger and less agile aircraft are used. When the former issue is approached with higher sensitivity at the radar receiver, the challenge moves to the automatic target recognition domain as the radar will be “flooded” by detection of many non-drones objects, including birds, trees swaying in the wind, and even ground vehicles that may be picked up by the side lobes of the radar [8-10].

To address these challenges, research activities have focused on achieving a better understanding of the electromagnetic signatures of drones, radar signatures specifically, and consequently on developing improved algorithms for their detection, tracking, and classification. In this paper, we report some results related to our research in developing better models of the signatures of small drones. Specifically, we present an approach for the electromagnetic simulation of propellers drones’ signatures developed at TU Delft (TUD), with the aim of generating synthetic micro-Doppler signatures that can be used to perform recognition tasks when combined with experimental data [11-12].

We also present some preliminary results aiming at modelling the radar signature of swarms of drones using the agent-based simulator MAVERIC developed at the University of Glasgow (UoG) [16-19]. MAVERIC is a bespoke multi-fidelity, multi-agent simulation engine developed to support research, development and system design within a systems engineering lifecycle framework. The added value of this simulator to the current project is the capability of describing in realistic detail the kinematics of small UAVs for different designs, thus improving the realism in their modelled electromagnetic signatures. An initial comparison of the signatures generated by the MAVERIC simulator and a few examples of experimental data previously collected with real radar systems are also performed, showing a good agreement between the data.

Both sets of results can contribute to the third topic of the Call for Papers of this specialists’ meeting, namely the “modelling relevant signatures for traditional detection methods”.

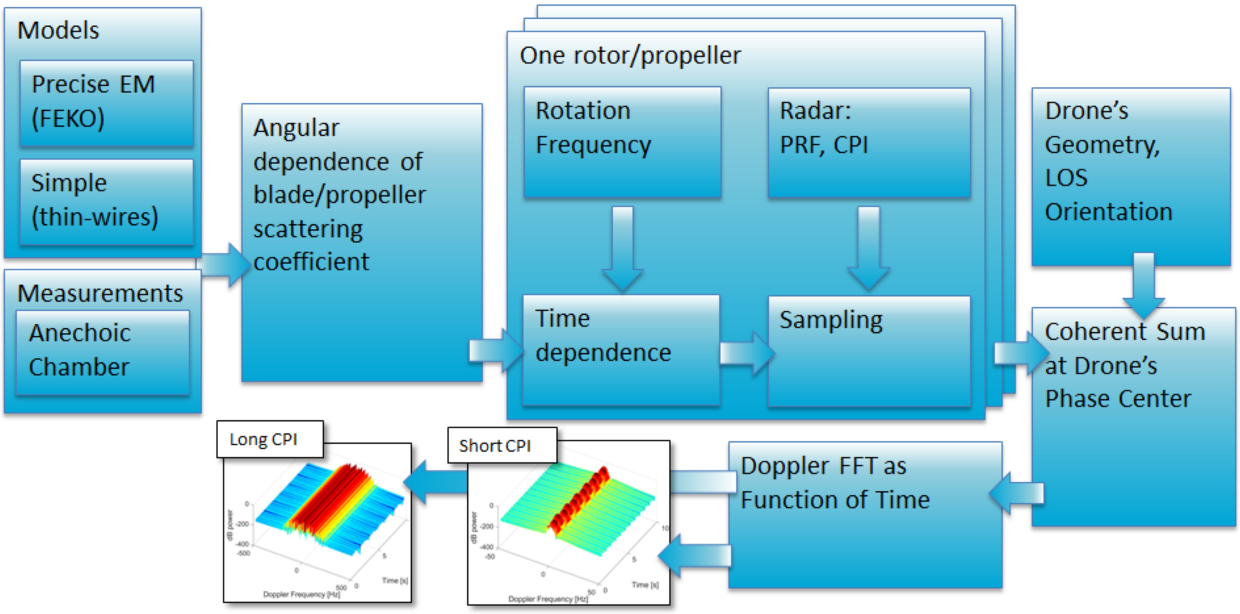

Figure 1 Block-diagram of the proposed general approach for the simulation of drone’s micro-Doppler pattern as a function of drone’s electromagnetic and dynamic characteristics, geometry, radar configuration and signal processing parameters.

2.0 APPROACHES

2.1 Simulations of multi-propellers drones radar signatures

In order to understand the relations of the observed radar micro-Doppler patterns for different drones in different flight scenarios with a variety of radars configurations, the signal processing parameters and properties of specific drone's rotating parts have been developed and tested in TU Delft as a general approach for the simulation of drones micro-Doppler patterns [11,12]. It is based on the angular patterns of drone body and propeller's scattering coefficient, which can be measured in an anechoic chamber, evaluated using exact electromagnetic solvers for specific 3D geometry of drone's parts, or simulated using their simplified thin-wires model (see Fig.1). The proposed approach can be easily and computationally-effectively applied for variable flight scenarios and radar configurations. It was used to study the influence of input data quality (the choice of model source) on the final micro-Doppler pattern [11]. The comparison with real radar measurements at S-band shows that the adapted for drone's propeller simulation simplified thin-wire model [13] demonstrates good agreement between observed and simulated micro-Doppler patterns in cases when the coherent processing interval is longer than the rotation period of drone's propellers (see Fig.2).

This very computationally efficient simplified thin-wire model uses a set of thin wires that follows to the edges of the original propeller 3D shape. The scattered field, in this case, can be written as in the following set of equations [11].

The symbol ~ indicates proportionality, $\eta = 120\pi$ is the intrinsic impedance of the atmosphere, $k = 2\pi/\lambda$ is the wavenumber, r_p is the distance between the propeller rotation center and an observation point. P is the number of propellers, B is the number of blades per propeller, W is the number of thin wires per blade in the simplified model, $dz'_{p,b,w}$ is the length of infinitesimal dipole along the z-axis at the distance $z'_{p,b,w}$ along the wth wire of the bth blade in the rotation plane. $l_{p,b,w}$ is the length of the wth wire of the bth blade in pth propeller:

$$\begin{aligned} E^{drone}(t,r_0) &\sim \sum_{p=1}^{P} E_p^{prop}(t,r_p,\theta_{p,b,w},l_{p,b,w}) \\ &= \sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{w=1}^{W} E_{p,b,w}^{wire}(t,r_p,\theta_{p,b,w},l_{p,b,w}) \\ &= \sum_{p=1}^{P}\sum_{b=1}^{B}\sum_{w=1}^{W}\int_0^{l_{p,b,w}} j\eta \frac{ke^{-jkr_p}}{4\pi r_p} \\ &\times E_{r_0}^{in}(t)\sin(\theta_{p,b,w}+\Omega_p t) \\ &\times e^{j2kz_{p,b,w}cos(\theta_{p,b,w}+\Omega_p t)} dz'_{p,b,w} \end{aligned} \quad (1)$$

The propeller rotates with the angular velocity Ω and all angles are changing in time linearly: $\theta(t) = \theta_{p,b,w} + \Omega t$, where $\theta_{p,b,w}$ is the initial angle of a specified wire relati-vely to the LOS at the initial time moment $t = 0$. W, $\theta_{p,b,w}$ and $l_{p,b,w}$ depend on the drone's design geometry.

To validate the thin-wire model of the multi-propeller drone and its micro-Doppler pattern, the real backscattered signal of the DJIM600 drone [14] was measured using the PARSAX radar system mounted on the roof of EWI (electronic engineering faculty) building at TU Delft campus [15].

The radar was configured to take full polarimetric measurements simultaneously at the centre frequency $f_c = 3.315$ GHz with pulse repetition frequency PRF = 1kHz. The dish antenna with a beamwidth of 1.8° was elevated for 0.9° to avoid ground clutter. The drone was hovering steadily within the beamwidth at the distance 9 km from the radar antennas. Micro-Doppler pattern of the drone was evaluated by applying 256-point STFT to a received signal series of 2 seconds with 128 points overlapped.

The drone micro-Doppler pattern was also generated from the thin-wire model. A synthetic backscattered signal series of 6 DJI R2170 propellers were generated with sampling frequency fs=1 kHz. These propellers assumed to rotate with random angle shifts at the same angular velocity of 3000 rpm. The model-based micro-Doppler pattern was evaluated by applying 256-point STFT to the generated signal series of 2 seconds with 128 points overlapped. Fig. 2 shows the normalized micro-Doppler patterns in HH polarisation measured by the real radar system and generated from the thin-wire model.

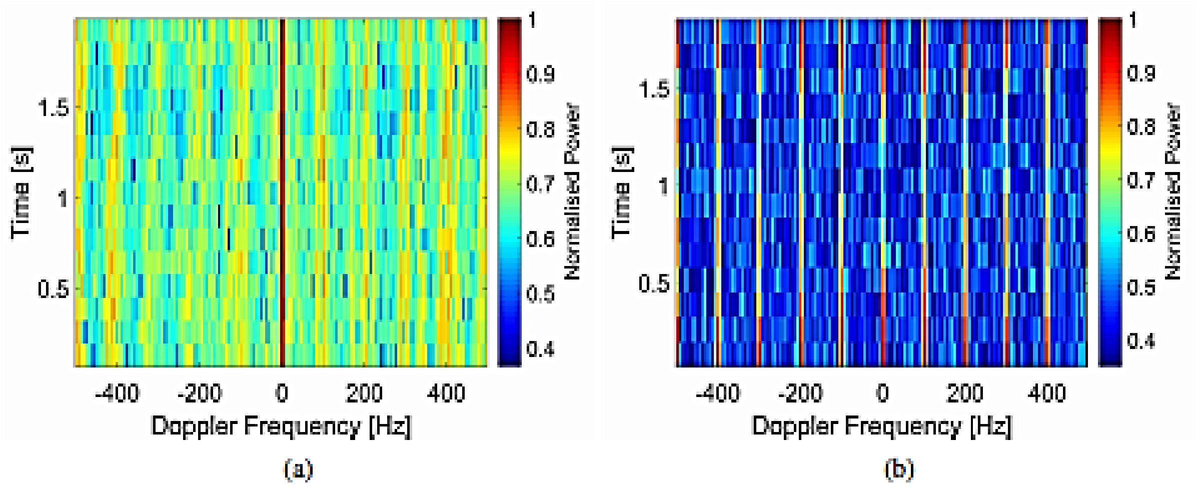

Figure 2 The micro-Doppler patterns of the DJI M600 drone: (a) Measured with the PARSAX S-band FMCW radar, (b) Simulated using simplified thin-wire model.

2.2 Simulations of behaviour of multiple drones

Introduced earlier, MAVERIC (Modelling of Autonomous Vehicles using Robust Intelligent Computing) is a bespoke multi-fidelity, multi-agent simulation engine which uses distributed artificial intelligence methods to simulate and perform various kinds of activities. MAVERIC uses an entity-container architecture which enables multi-fidelity models of both sensors [17] and platforms [16] to be simulated and has recently been applied to radar systems operation [18,19]. Using MAVERIC, one can efficiently generate multiple drone trajectories and attitudes/behaviours based on various scenarios of interest. For the computational efficiency, simulation models will be assigned to multiple threads, which are based on the multiple cores of a CPU or a GPU.

MAVERIC enables to model with fine details the kinematics of different aircraft, from helicopters to small UAVs, which are of interest in this paper. In particular, it is possible to describe the 3D position and velocity over time of a large number of points for each object to be modelled. These points can then be considered scattering centres and their associated radar signatures can be calculated.

The chosen radar signal model will be also simplified for computational efficiency. A radar reflecting surface on a drone's body or on a blade can be considered to be a single scattering point (or more), with an associated fixed or probabilistic Radar Cross Section, RCS (according to an underlying model or distribution). For the generation of micro-Doppler signal, the position and velocity of drone's blades can be calculated with simple kinematic relations.

3.0 PRELIMINARY RESULTS

Regarding results from the MAVERIC simulator, initial proof of concept results are generated in MATLAB and then will be translated and expanded into the C++ core implementation of MAVERIC.

Fig. 3 shows the simulation result for a three drones scenario. The drone 1 and 3 are fixed-wing UAVs and the drone 2 is a quadcopter. Fig. 3(a) shows the flying trajectories of each drone. The drone 1 moves in a circular trajectory while the drone 3 moves along a straight trajectory. The drone 2 is loitering in a relatively small area. In perspective, the drone 1 may represent a lower risk activity where the platform could be filming or inspecting an area, whereas the drone 3, with straight-on flying trajectory, could model a more risky behaviour if heading towards a restricted area or asset. While these assumptions are of course scenario-dependent and not conclusive, the results shown here serve the purpose of demonstrating the aspirational capabilities of the simulator.

Fig. 3(b) is a range-time radar plot and Fig. 3(c) is the corresponding micro-Doppler signature (Doppler vs time plot) for the scenario. We can observe the HERM (HElicopter Rotor Modulation) lines generated by the drone 2. The HERM line phenomenon occurs when the rotational speed of a rotor is too high to capture by the given radar parameters for the micro-Doppler analysis. Fig. 3(d) shows a snapshot of the range-Doppler plot and we can see two distinguishable signatures in the range-Doppler at 12.9s.

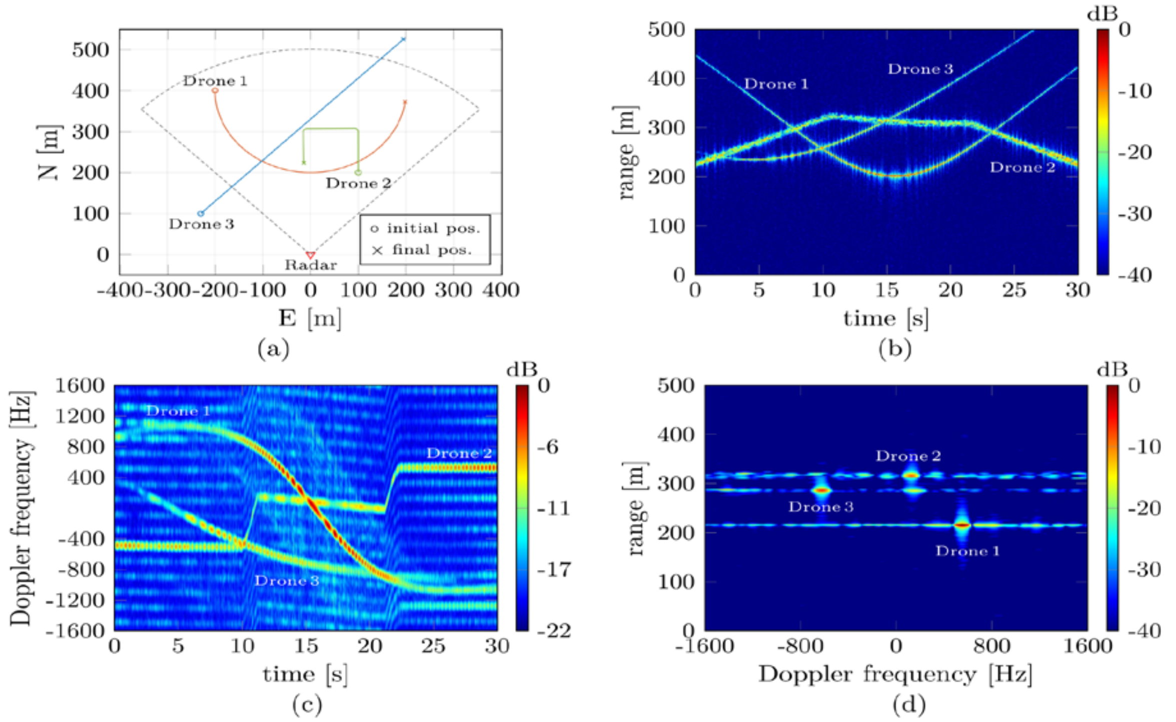

Figure 3 Example of preliminary simulation results with 3 drones: (a) Trajectory sketch, (b) Range-time plot, (c) Micro-Doppler spectrogram, (d) Range-Doppler snapshot at time 12.9s

It should be noted that this simulation is still very simplistic, with each drone modelled by a limited number of scattering points (one for the drone body and one for each blade) and the multipath effect was not considered. The RCS of each scattering points has been set by the Swerling model, which determines the RCS by using the chi-squared distribution. Ongoing work aims to increase the kinematic fidelity of the movements modelled in the simulation, as well as their electromagnetic fidelity (e.g. multipath interference, antenna pattern of the radar, increased number of scattering points).

To further validate the performance of the MAVERIC, two experimental results were used as reference data. The first experiment was conducted using the multistatic pulsed radar system, NetRAD, developed by University College London and University of Cape Town [20]. Fig. 4 shows both experimental and simulated data of the experiment. The target was a DJI Phantom quadcopter hovering at approximately 70m away from the radar. Fig. 4(b) shows the simulated range-time plot and we can confirm that the signature of the quadcopter is located at 70m and the tree clutter simulated at around 280m is similar to the real experimental data, in Fig. 4(a).

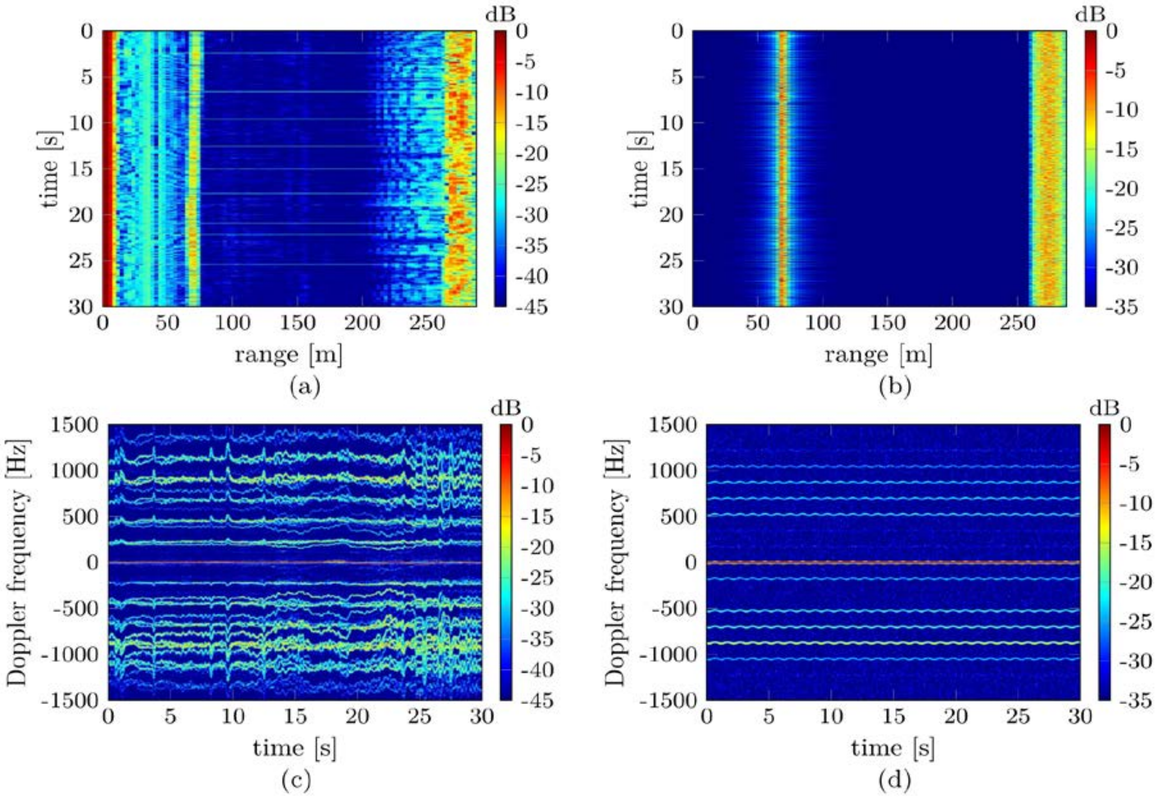

Figure 4 Comparison between experimental data (NetRAD) and MAVERIC: (a) Range-time intensity (NetRAD), (b) Range-time intensity (MAVERIC), (c) Micro-Doppler spectrogram (NetRAD), (d) Micro-Doppler spectrogram (MAVERIC)

In the Fig. 4(c), the experimental HERM lines are fluctuating due to the vibration of the quadcopter itself because of the wind during the data collection. An initial attempt to capture this characteristic is here implemented through a simplified vibration model based on the sinusoidal acceleration of the drone's CG (Center of Gravity). More complex and more realistic models can be applied as part of further refinement of the simulator. Compared with the real spectrogram on Fig.4(c), the simulated spectrogram on Fig.4(d) shows similar HERM line distribution with respect to the Doppler gap between lines and the relative intensity of each lines, which is a satisfactory initial result.

The second experiment was conducted using the PARSAX S-band FMCW radar [21]. The target of the radar was a hexacopter approaching the radar at a speed of 5.8m/s which is equivalent to a Doppler frequency of 128 Hz. Fig.5(a) and (b) show the range-Doppler map of the experimental and the simulated data, respectively. The line on 0Hz of the graph is the signal from the static clutter contributions, such as buildings and ground reflections. Other than the static clutter's signal, the signature with highest intensity exists on the Doppler frequency of approximately 128Hz and the range of 7.87 km. The main contribution of the signature was generated by the scattering points of the hexacopter's fuselage while the signals spreading all over the Doppler frequency which have relatively low intensity was generated by scattering points of the rotating blades. Fig.5(a) and (b) appear to be similar with each other, showing acceptable capabilities of the proposed simulator to mimic examples of realistic data.

As the previous results have shown that the MAVERIC simulator can generate synthetic data with sufficient fidelity compared to experimental data, additional simulations for three drones in formation flight were performed and reported here. The idea is to mimic what the real aforementioned two radar systems, NetRAD and PARSAX, would observe in such situations.

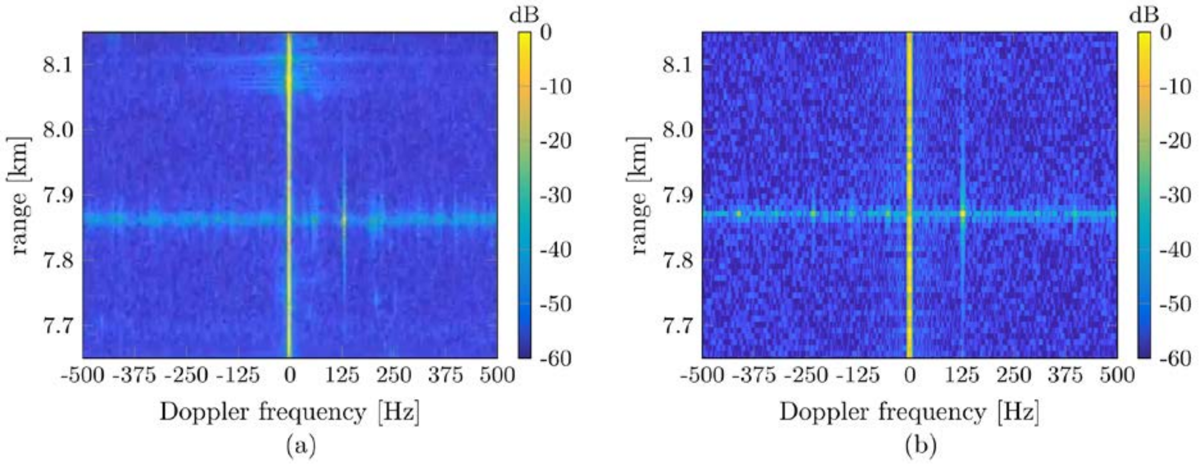

Figure 5 Comparison between experimental data (PARSAX) and simulated MAVERIC data for a hexacopter drone flying at approximately 9km: (a) Range-Doppler map (PARSAX), (b) Range-Doppler map (MAVERIC)

For the NetRAD simulation, initial conditions of three quadcopters were set as in Fig. 6(a) with three drones close to each other and their formation located at about 200m from the radar. Fig. 6(b) shows the range-Doppler map of the simulation and two lines are clearly separated. The drone 1 caused a range-Doppler contribution near 200m and the drone 2 and 3 range-Doppler signals were overlapped at around 220m. This is expected because the radar does not have angular estimation capabilities and drone 2 and 3 keep equal distance from the radar in the simulation.

For the PARSAX simulation, initial conditions of three hexacopters were set as in Fig. 7(a).

Unlike the result of the NetRAD simulation, range-Doppler map of the PARSAX simulation (Fig. 7(b)) shows only a single target signal due to the size of the range bin. This shows that for the given specification of the PARSAX, it may be difficult to distinguish between single platforms or multiple drones close to each other in some circumstances.

As a further test of the usefulness of good synthetic data for radar-based drone monitoring, preliminary results of the TUD EM model of the micro-Doppler signatures are used for classification. The general approach for the simulation of drones' micro-Doppler patterns in combination with the simplified thin-wire model of drone propellers was described in section 2.1. This has then been used in [12] for a feasibility study of multi-propeller drones radar recognition. The model has been used for the simulation of observed during long (in terms of propeller rotation period) CPI micro-Doppler linear spectra of quadcopters and hexacopters.

Different multi-dimensional sets of features extracted from such spectra for the recognition of these two types of drones have been investigated. As an example, in Fig.8 we present the distribution of observations of hovering drones in this 3D space of features, which are derived from the set of harmonics lines amplitudes in micro-Doppler spectra. The confusion matrix is also presented in the same figure, showing very good results in terms of performance metrics.

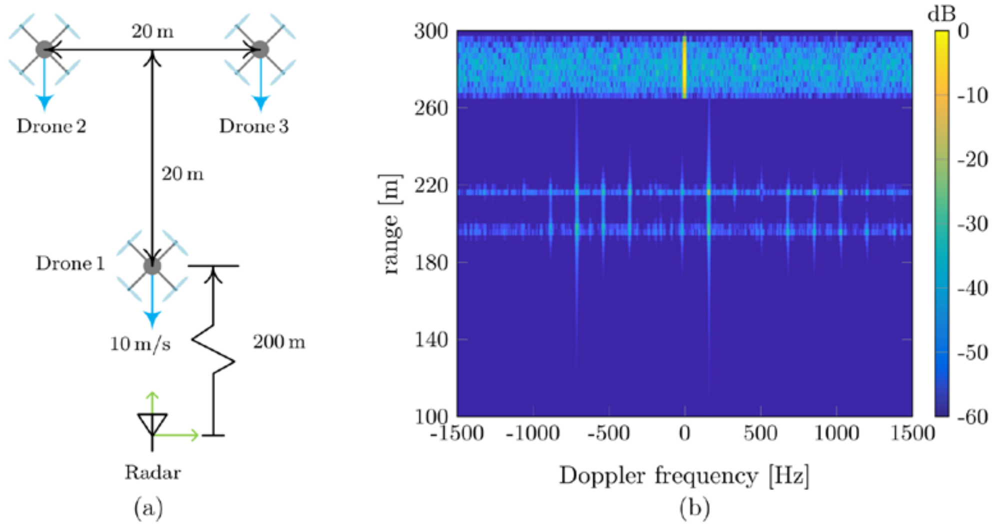

Figure 6 NetRAD simulation result for three drones (quadcopter) in formation flight: (a) Configuration of formation flight, (b) Range-Doppler map (MAVERIC)

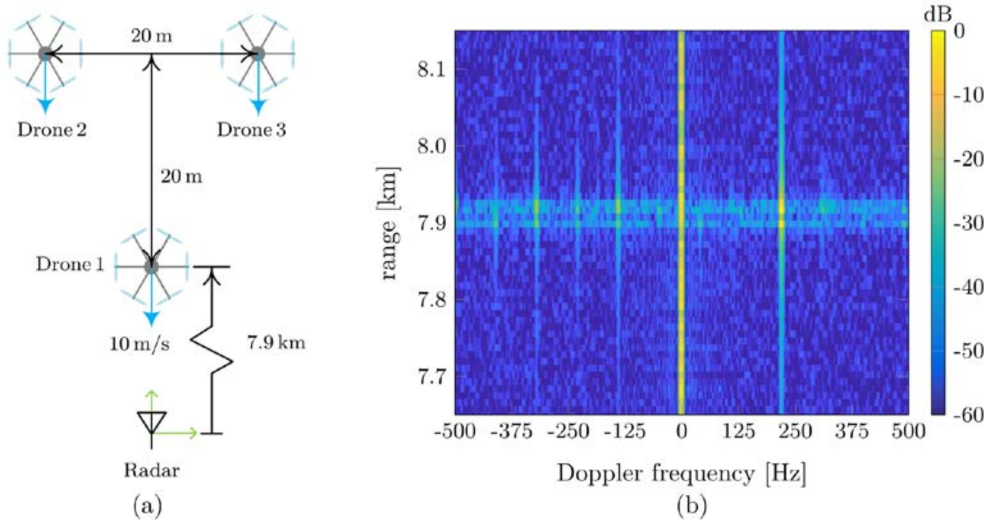

Figure 7 PARSAX simulation result for three drones (hexacopter) in formation flight: (a) Configuration of formation flight, (b) Range-Doppler map (MAVERIC)

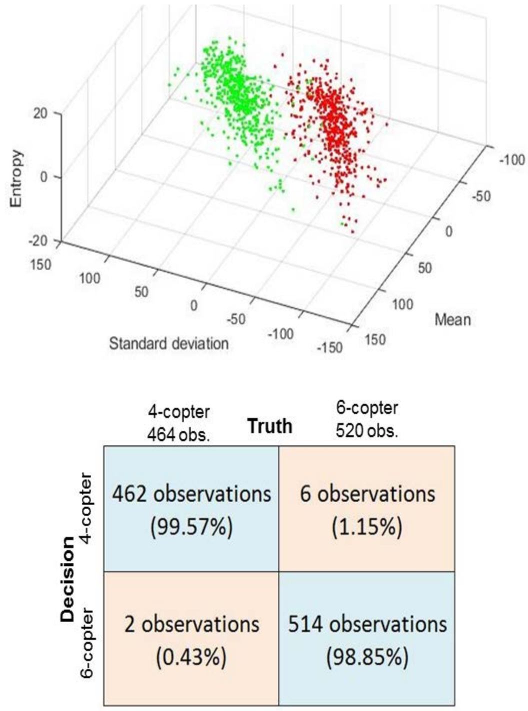

Figure 8 Results of drone recognition using features that derived from the set of amplitudes of harmonic lines in the simulated micro-Doppler spectra patterns in a hovering flight mode.

4.0 CONCLUSIONS AND FUTURE WORK

This paper has presented initial results from ongoing research activities at TU Delft, the Netherlands, and at the University of Glasgow, UK, to achieve a better understanding of the radar signatures of small drones. Better modelling capabilities and the generation of good synthetic data are key to develop and enhance algorithms for the detection, tracking, and classification of this emerging class of targets.

The paper has briefly described the models and the principles of the simulators, with reference to publications for further details. An initial comparison of the data simulated by the UoG MAVERIC with experimental data using two different radar systems, namely the NetRAD and the PARSAX, have been shown. Good visual agreement and the value of key metrics in the range-Doppler and range-time domains have been achieved. This is promising, although additional work is needed to increase the fidelity of the simulator. Mainly, this can be articulated into two aims for further work. On the one hand a better electromagnetic scattering model is needed to represent the interaction of the drone parts with the impinging and reflected waves. On the other hand, the kinematic of the movements of the drones can be represented with finer details, for example including the vibrations and the small oscillations performed by these platforms in real conditions on top of the desired main trajectory. Furthermore, work is ongoing in modelling with the fidelity the swarm behaviour of multiple drones, i.e. capturing correctly how the movement of one platform/agent influences the others in a given simulation.

The paper has also shown the good fidelity of the TUD thin-wire EM model to represent blades of small drones in the micro-Doppler signatures, and how these can be used to complement experimental data in classification problems.

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